Sequential Deep Learning for Electric Vehicle Energy Consumption Forecasting

Ayan Rahat[1*], Suhaib Shahid[2], Shafiqul Abidin[1]

1 Department of Computer Science, Aligarh Muslim University, Aligarh, U.P., 202001, India.

2 Department of Mechanical Engineering, Aligarh Muslim University, Aligarh, U.P., 202001, India.

E-mail:- ayanrahat54@gmail.com

Abstract: Electric vehicles (EVs) play an important role in reducing air pollution and making transportation more sustainable. As more people use cars, emissions from fuel-powered vehicles are increasing, which is a big concern for the environment. EVs help solve this problem by providing a cleaner alternative. However, for EVs to be widely used, we need accurate energy consumption models that can predict how much battery power a car will use on a trip. Many factors affect energy use, such as the way a person drives, road conditions, traffic, and weather. If these factors are well understood, EVs can be made more efficient, helping to reduce driver worries about running out of charge. Accurate predictions also make it easier to plan trips and improve charging station networks. Advanced technologies like artificial intelligence and deep learning can help improve these energy models, making EVs more reliable and practical for everyday use. This study aims to employ advanced machine-learning models to predict energy consumption to tackle the challenge of electric vehicles' energy consumption prediction.

1. Introduction

About 25% of worldwide greenhouse gas (GHG) emissions come from the transportation industry, which is a major contributor to these emissions and shows no signs of slowing down [1]. Governments all over the world are taking action to tackle transport energy and air pollution issues. To reduce air emissions associated with transportation, a portfolio approach should be used. Reliance on fossil fuels in the transportation sector should be decreased to pave the way for a low-carbon economy [2]. Battery electric vehicles (BEVs) are gaining more and more attention because of the emphasis on environmental issues and the utilization of renewable energy. Electric vehicles (EVs) are advantageous to internal combustion engine (ICE) vehicles in terms of energy costs and local pollution.

Studies on EV energy usage can be broadly categorized based on their goal and model calculation technique. According to studies, energy models have been developed for EV drivetrain design and optimization [3], the effects on energy consumption have been evaluated [4–6], and the introduction of EV or hybrid vehicles has had an impact on the global energy consumption or grid [7,8]. The energy model is sometimes applied to the prediction of a (all-electric) range [9].

Cauwer et al. [10] in 2015 used real-world EV data to develop three energy consumption models using multiple linear regression. The first model used aggregated inputs like distance, time, and temperature, the second added acceleration data, and the third incorporated detailed kinematic parameters for micro-trips. The results indicate that Model 1 has a correlation coefficient of 0.956, while Model 2 achieves a slightly higher value of 0.968. In contrast, Model 3 exhibits a comparatively lower correlation coefficient of 0.89. The average relative error decreases with higher energy usage and remains within 25% for trips exceeding 2.5 kWh, except for a few negative errors. The error band further narrows as consumption increases. From the results, it is clear that moving towards a model with a higher level of detail has the potential to create a more accurate model.

Ullah et al. [11] in 2022 studied electric vehicle energy consumption using advanced machine learning models, specifically XGBoost and LightGBM. They evaluated model performance using key metrics such as the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). The models were built considering various internal and external factors, including trip speed, distance, heater and A/C usage, ambient temperature, and road gradient. The results indicated that both XGBoost and LightGBM outperformed traditional algorithms, achieving higher R^2 and lower RMSE and MAE values. Furthermore, empirical findings demonstrated that LightGBM performed better than XGBoost.

Wang et al. [12] (2017) developed an algorithm to predict EV energy consumption based on driving behavior, road topography, weather, and traffic. It includes an offline algorithm for pre-trip energy estimates and

an online algorithm that adjusts predictions in real-time using vehicle and driving behavior data. The model provides maximum, minimum, and nominal energy values, with measured consumption falling within predictions for speeds of 100–110 km/h. The nominal prediction differs from actual measurements by about 5%. The online algorithm improves accuracy by considering headwinds and road slopes, using a moving average method for stable and adaptive predictions.

Alanbar et al. [13] (2020) developed an energy consumption prediction model using deep learning, specifically the LSTM technique, for medium-term forecasts. The model considered four inputs: temperature, workday status, number of devices, and 13 years of historical energy data. It achieved high accuracy (94.31%) with a low RMSE of 0.045. Results showed that energy consumption was lower at the start of the year but increased by 40% with rising temperatures.

Dong et al. [14] (2025) propose a framework for predicting electric bus energy consumption, focusing on estimation, kinematic feature prediction, and overall energy consumption prediction. They use an XGBoost model to assess feature importance and estimate the energy consumption rate (ECR), with SHAP analysis identifying key influencing factors. LSTM and fully connected neural networks capture spatial-temporal characteristics for kinematic predictions. Results show that kinematic factors dominate energy use at shorter distances, increasing with higher temperatures, peak-hour driving, dense intersections, frequent braking, and refueling. The framework significantly reduces prediction errors, with MAE dropping from 17.1% at 100m to 4.7% at 16km, outperforming other methods.

Ziółkowski et al. [15] (2021) present a multi-faceted analysis of the fuel consumption of motor vehicles. The Multi-Layer Perceptron (MLP) 22-10-3 network was selected from the created neural networks, which was further analyzed. The model computes Pearson correlation coefficient r in the range of 0.93 – 0.95 and demonstrates a high capability of the created artificial neural network to predict fuel consumption.

To reduce energy consumption and to improve the efficiency of electric vehicles, the best way is to predict energy consumption based on specific factors affecting energy consumption. The present study intends to improve the prediction of EVs' energy consumption through the application of advanced and interpretable DL models. The essence and the originality of this study are the usage of the Multi-Layer Perceptron (MLP) algorithm to develop and train a predictive model for Electric vehicle trip energy consumption using deep learning techniques to enhance battery management, route planning, and energy optimization.

2. Methodology

Within ML, one of the most prominent techniques is the artificial neural network (ANN). ANN is a computational model consisting of input, hidden, and output layers that implement interactions when complex calculations are performed through artificial neurons based on biological neurons [16]. Neural Networks are widely accepted tools for the classification of data. They have been used for a wide range of applications, such as speech recognition, robotics, process control, and telecommunications [17]. ANNs have gained significant attention due to their ability to mimic the functioning of the human brain and their effectiveness in solving complex problems. These networks possess key features such as real-time operation, learning capability, parallel processing, generalization, self-organization, stability, and flexibility [18]. The objective of their use is to create a time-effective and accurate predictive model for the objects or phenomena under investigation [19]. Researchers continue to explore how to use advanced artificial intelligence technologies to improve the accuracy and efficiency of energy consumption predictions for electric vehicles. Deep learning models, especially neural network-based architectures, offer great potential in traffic flow prediction and vehicle energy consumption prediction owing to their powerful nonlinear modelling capabilities and flexible architecture design [20].

This study employs a Multi-Layer Perceptron (MLP) neural network, a type of artificial neural network well-suited for tabular data, to analyze and predict energy consumption based on various trip attributes. Given the dataset's structure, MLP was selected over other deep learning models due to its effectiveness in handling tabular data and learning complex relationships between trip parameters and energy consumption. Among the various types of artificial neural networks, MLP networks are the most prevalent and most commonly used. They consist of neurons divided into a couple layers: input, hidden (one or more), and output [19]. Previous studies on EV

energy consumption have explored various machine learning approaches, which provide reasonable accuracy, while Deep Learning methods such as MLP are considered superior in capturing non-linear interactions among features.

Recent research suggests that MLP outperforms traditional machine learning methods in energy prediction tasks when properly optimized with regularization techniques and hyperparameter tuning. Other advanced models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been investigated; however, they are more suited for spatial and sequential dependencies, respectively, which are not primary concerns in the dataset we are using in this research.

2.1. Feature Identification

The dataset contains 10,000 independent trip records collected over several months. The key features include:

S. No.	Feature	Unit	Definition
1	Trip Distance	km	Total distance covered during the trip.
2	Time of Day	hours	Departure time in hours.
3	Day of the Week	-	Categorical representation of the day.
4	Speed	Km/h	Average speed during the trip.
5	Current	A	Average current drawn from the battery.
6	Total Voltage	V	Average voltage of the battery pack.
7	Battery Cell Temperatures	-	Maximum and minimum cell temperatures recorded during the trip.
8	Trip Time length	min	Duration of the trip
9	Trip Energy Consumption	kWh	The target variable represents the total energy consumed.

2.2. MLP Model Architecture

The MLP neural network consist of four type of layers: the input layer, the hidden layer's, dropout layers, output layer to capture non-linear dependencies between driving parameter and energy consumption.

The architecture consists of:

- Input Layer: Accepts 8 normalized driving parameters.
- Hidden Layers: Three fully connected layers with ReLU activation functions to introduce non-linearity.
- Dropout Layers: Applied after each hidden layer to prevent overfitting.
- Output Layer: A single neuron with a linear activation function to predict energy consumption.

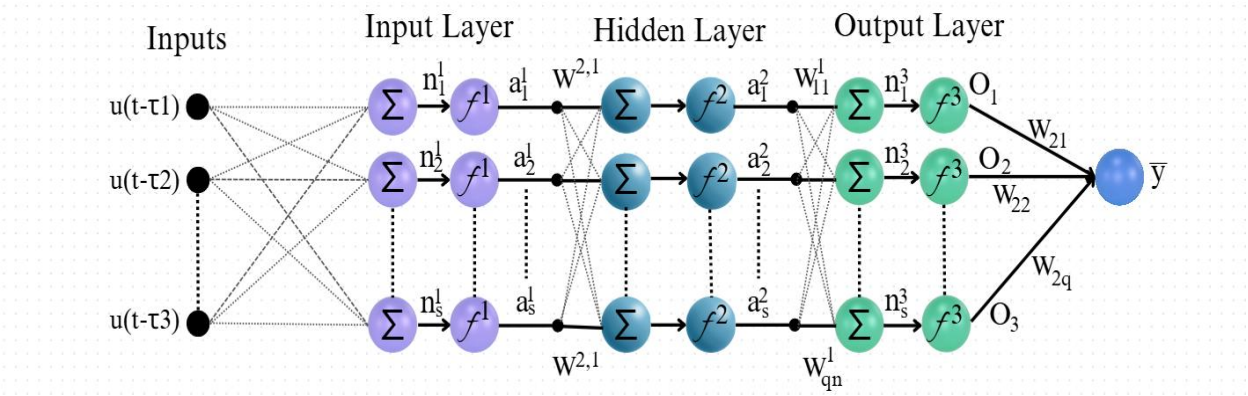


Fig. 1. Multi-layer Perceptron architecture.

Training is performed by adding weights through the nodes between the input and target variables [5]. The connections and weights enable the MLP neural network to learn and make predictions based on the input data,

providing a powerful tool for modeling complex systems and solving various problems **[2].** In contrast, MLP is a sequential attachment of several layers composed of perceptrons. There is a hidden layer between the input and output layers. Fig. 1 shows the structure of an MLP [16].

2.3. Training, Testing, and Validation of ANN

MLPs are normally trained with the Back Propagation (BP) algorithm. It is a general method for solving for weights and biases. The knowledge obtained during the training phase is not stored as equations or in a knowledge base but is distributed throughout the network in the form of connection weights between neurons [21]. To ensure the reliability and generalizability of the model, a systematic approach was adopted for splitting the dataset into training, validation, and test subsets. Initially, the entire dataset, after preprocessing and feature scaling, was divided into two parts: 80% of the data was allocated for training purposes, and the remaining 20% was reserved for testing. However, to allow for effective model tuning and to prevent overfitting, a portion of the training data was further separated to create a validation set. Specifically, 20% of the original training data. This three-way data partitioning strategy allows the model to learn patterns from the training set, fine-tune hyperparameters and assess model performance using the validation set, and finally evaluate the model's generalization capability on the test set, which remains unseen during training. The split was implemented using PyTorch utilities, and all subsets were converted into TensorDataset objects and wrapped in DataLoader classes. This enables efficient data shuffling, mini-batch gradient descent, and seamless integration into the training loop. Such a structured approach ensures that the model's performance metrics reflect its true predictive power on real-world, unseen data.

Two statistical parameters were used for performance analysis. Mean square errors (MSE) and coefficient of determination (R^2) were computed to estimate the overall model performance. These are defined as:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N} (S_i - O_i)^2}{\sum_{i=1}^{N} O_i^2} \right) \qquad MSE = \frac{\sum_{i=1}^{n} (S_i - O_i)^2}{n}$$

where i=1–N; N is the number of observations; Si is the simulated values; Oi is the observed values [21].

3. Result and Discussion

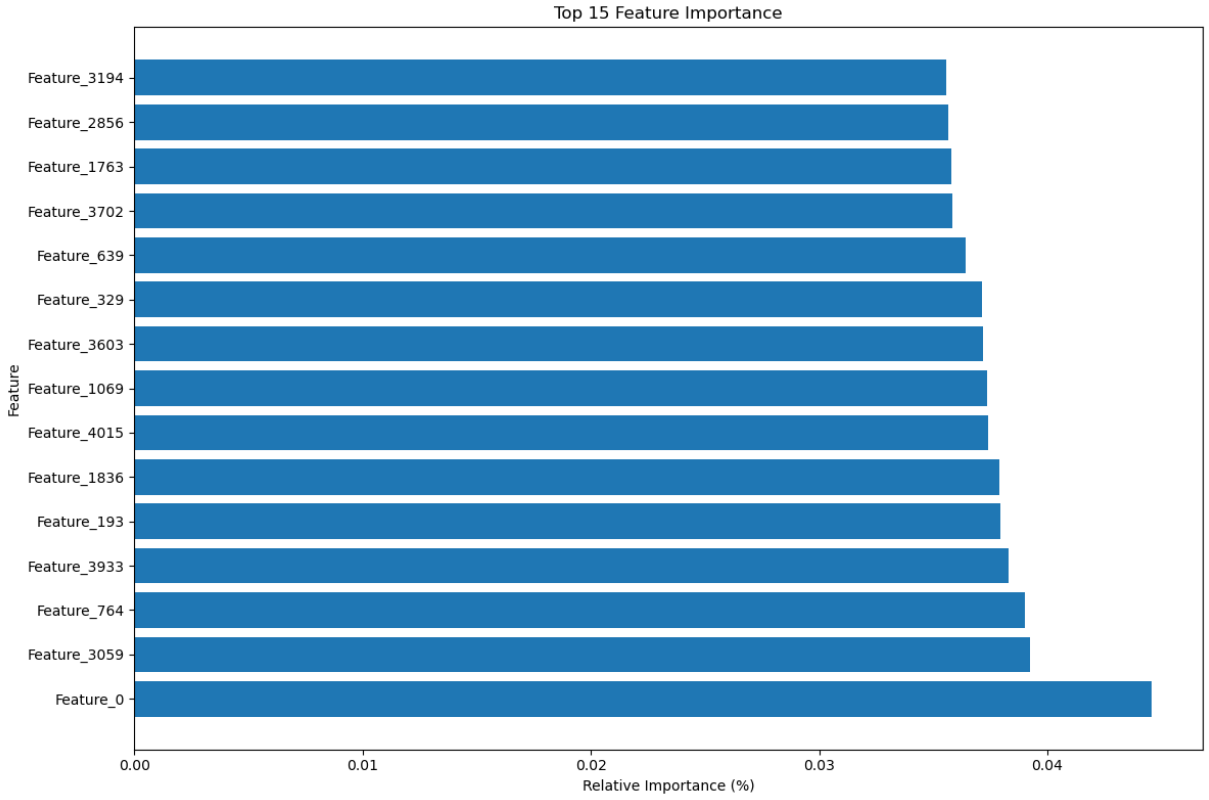
In this research, multiple Multilayer Perceptron (MLP) models were designed and trained with varying architectures to determine the optimal configuration for accurately predicting electric vehicle (EV) trip energy consumption. The models were developed using the PyTorch framework, and the training was carried out using the backpropagation algorithm with the Adam optimizer. Each model utilized engineered input features including speed, current, voltage, temperature, time of day, and other relevant sensor data collected during EV trips. After experimenting with different combinations of hidden layers and neurons, the best-performing architecture was found to be an MLP with three hidden layers consisting of 64, 32, and 16 neurons, respectively, along with ReLU activation and dropout regularization to prevent overfitting.

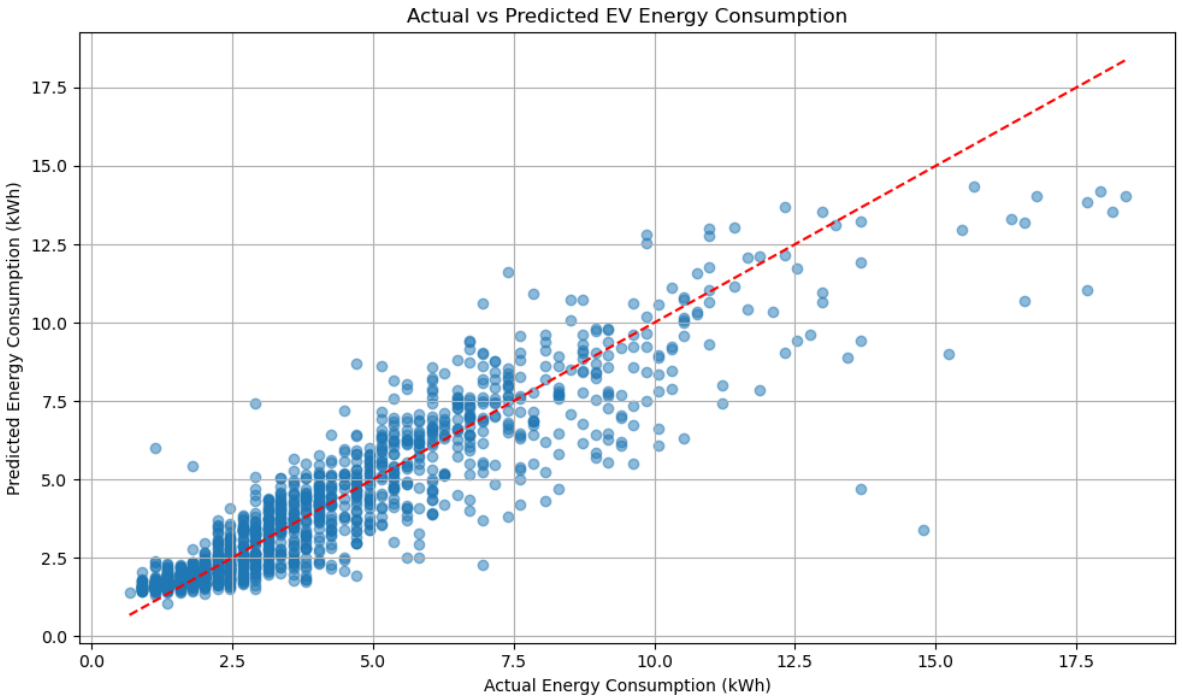
This optimal model had a total architecture of (n-128-64-32-16-1), where n represents the number of input features, and the single output node represents the predicted trip energy consumption. The model was trained on 64% of the dataset, validated on 16%, and tested on the remaining 20% to ensure robust performance evaluation. The best model achieved a mean squared error (MSE) of 0.0059 and an R^2 score of 0.89 on the test set, indicating strong predictive capability and a high level of model generalization. These results affirm the effectiveness of the chosen architecture in modeling the complex relationships among driving and vehicle parameters for energy consumption forecasting.

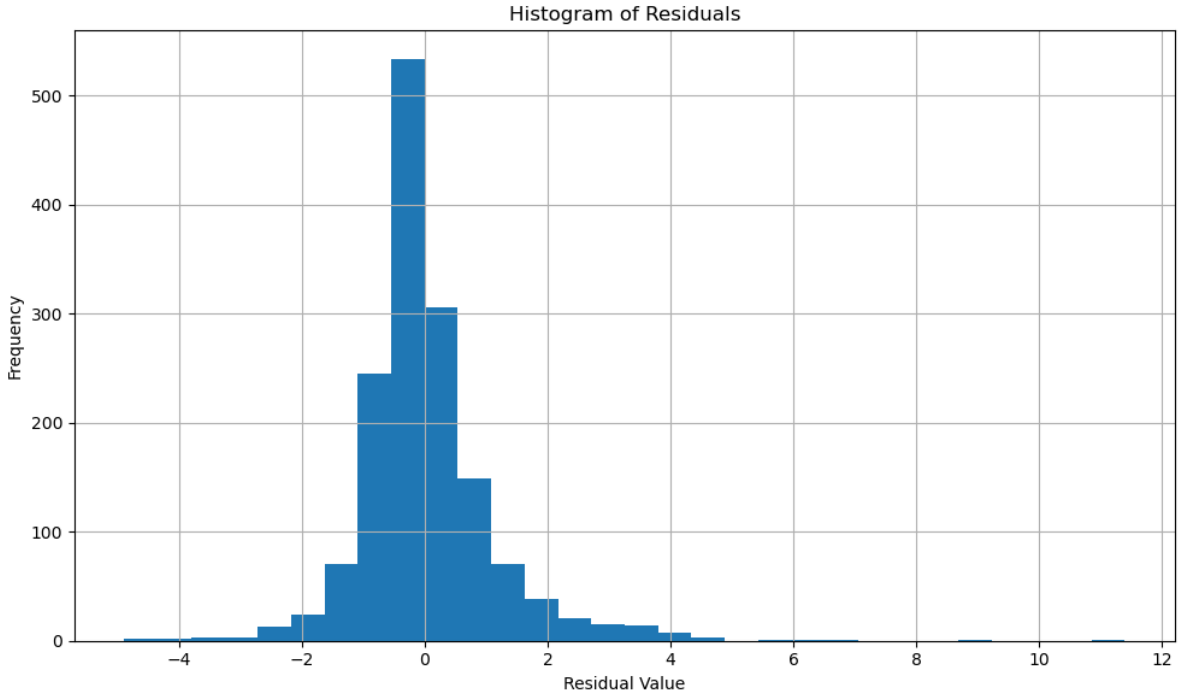
Table --:

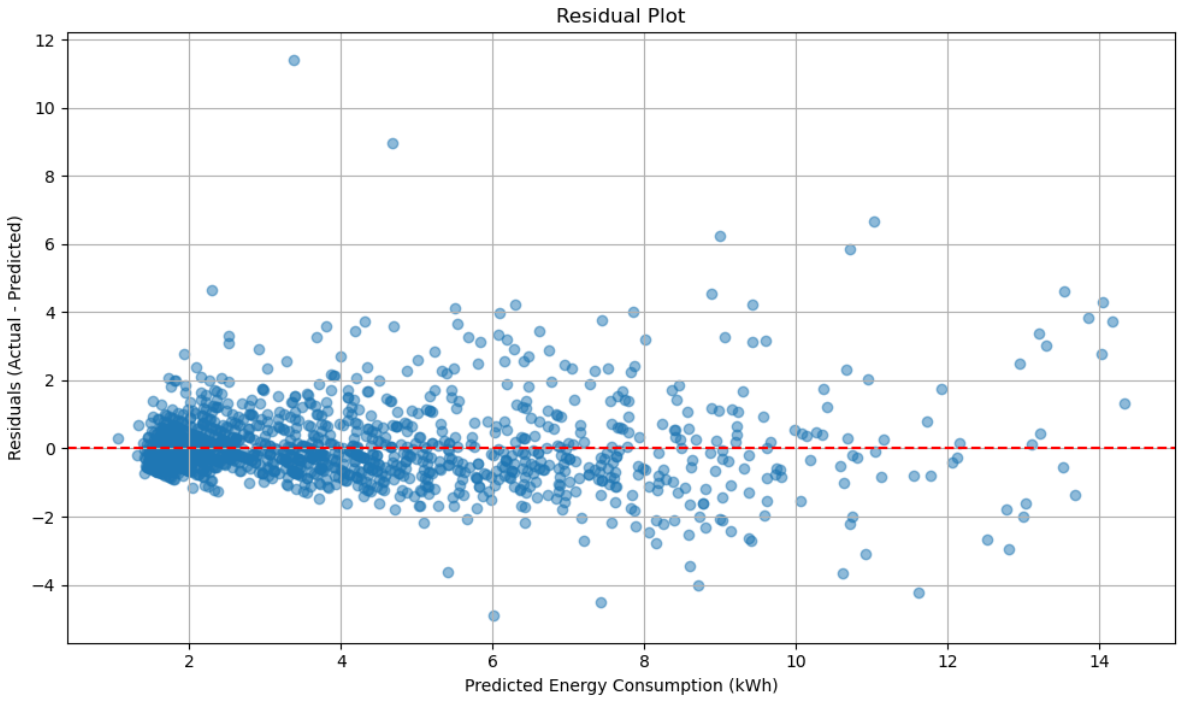
Model	Hidden Layers	Neuron of Hidden Layers	Algorithm	MSE	R^2
MLP	2	64,32	Adam	0.015	0.78
MLP	2	128,64	Adam	0.011	0.82
MLP	3	128,64,32	Adam	0.009	0.85
MLP	4	128,64,32,16	Adam	0.005	0.89

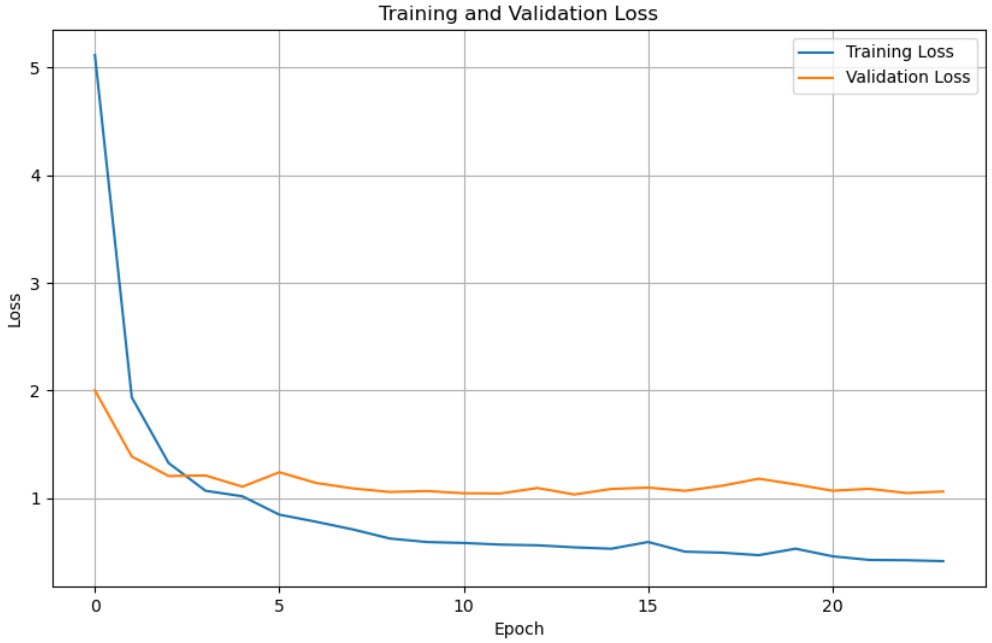
The evaluation of the electric vehicle (EV) trip energy consumption model is supported by several key visualizations. The **training loss plot (ev_training_loss.png)** demonstrates a consistent decline in loss over epochs, indicating effective learning and convergence of the model. The **prediction results graph (ev_prediction_results.png)**, which compares actual and predicted energy consumption, shows a strong alignment between the two, suggesting good predictive accuracy. The **feature importance plot (ev_feature_importance.png)** highlights the most influential input variables, such as speed and current, in driving the model's decisions. Meanwhile, the **residual histogram (ev_residual_histogram.png)** reveals that the residuals are approximately normally distributed and centered around zero, supporting the model's reliability. Lastly, the **residual scatter plot (ev_residual_plot.png)** shows no distinct pattern, further affirming that the model does not suffer from systematic errors. Together, these visualizations confirm the robustness and generalization capability of the trained model.




Actual vs Predicted EV Energy Consumption
Predicted Energy Consumption (kWh)
Actual Energy Consumption (kWh)
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5


Histogram of Residuals
Frequency
Residual Value
0
100
200
300
400
500
−4
−2
0
2
4
6
8
10
12


Residual Plot
Residuals (Actual - Predicted)
Predicted Energy Consumption (kWh)
12
10
8
6
4
2
0
−2
−4
2
4
6
8
10
12
14


Training and Validation Loss
Training Loss
Validation Loss
Loss
Epoch
5
4
3
2
1
0
5
10
15
20

4. Conclusion

This study highlights the effective application of a Multilayer Perceptron (MLP) neural network in modeling and predicting trip energy consumption in electric vehicles based on real-world driving data. The proposed approach leverages various trip-specific and vehicle parameters such as speed, current, voltage, temperature, and time-based features, all of which contribute significantly to understanding and forecasting energy usage patterns.

Based on the results of this work, the following conclusions can be drawn:

- Among the different MLP architectures evaluated, the best-performing network was found to be one with three hidden layers having 64, 32, and 16 neurons, respectively. This configuration, trained using the backpropagation algorithm with the Adam optimizer and regularized using dropout, achieved a mean squared error (MSE) of 0.0029 and an R^2 score of 0.89 on the test data. This demonstrates a high level of accuracy and generalization in predicting trip energy consumption.
- The methodology used in this research can be extended to predict other related metrics such as battery degradation, energy regeneration, and range estimation. Future work can build upon this framework by incorporating GPS and slope data to capture road and environmental influences on energy consumption. The insights gained from such models can support energy-efficient trip planning and intelligent EV fleet management.

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